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BAYESIAN PREDICTION OF MEAN SQUARE ERRORS WITH COVARIATES

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BAYESIAN PREDICTION OF MEAN SQUARE ERRORS WITH COVARIATES

by P. A. Jacobs and D. P. Gaver

1. INTRODUCTION AND SUMMARY

Numerical meteorological models are used to assist in the prediction of weather. Each run of a numerical model produces forecasts of meteorological variables which are used as preliminary predictions of future values of these variables. These initial predictions are referred to as first-guess values. In this paper first-guess values will refer to the most recent 12-hour forecasts.

In certain areas of the world, observations of forecasted variables become available. Prior to the next run of the numerical model a multivariate optimal interpolation analysis updates a first-guess value of a variable by adding to it a weighted observed value of the variable if it is available. The weight multiplying the observed value depends on estimates of the mean squared error of the first-guess value and the mean squared error of the observation; cf. Goerss et al., [1991, a, b]. Thus it is of importance to predict such first-guess squared errors.

The general problem of modeling and predicting mean square errors is important but not widely studied; see Davidian and Carroll (1987), Nelder and Lee (1992), Aitken (1987), McCullagh and Nelder (1983).

In Jacobs and Gaver (1991, 1992) statistical models for the error of the first-guess are used to predict mean square error for first-guess wind components. The models assume that the error of the first-guess is normal with mean 0

and variance which is a function that is log-linear with suitable covariates. The cross-validation results of those papers suggest that covariates do have some predictive ability for the mean square errors. However, the relations change over time.

In this paper we introduce a procedure for recursively updating the estimated parameters of the variance function. The approach is Bayesian with recursive updating using an approximation based on the Laplace method; cf. deBruijn (1958).

In the next section the model is introduced. Details of the updating procedure are also given.

The third section presents results of using the procedure to predict mean square first-guess wind component errors. The data consist of measurement and 12 hour forecasts (first-guess values) of u and v wind components at 850 mb, 500 mb, and 250 mb pressure levels from 93 stations in North America, 25N-75N. The measurement values (if available) are subtracted from the first-guess values to obtain observations of the first guess error. The covariates considered are wind speed and resultant wind, (the sum of the squared difference of the u --wind component at two consecutive 12 hour periods and the squared difference of the v -wind component at the same times). The resultant wind is a measure of the change in the atmosphere. Higher wind speeds suggest more activity in the atmosphere.

The results of the data analysis suggest that the covariates do have predictive ability. The models using observed wind speed and resultant wind have more predictive ability than those using the first-guess values of wind speed and resultant wind. Further, models that use both wind speed and

resultant wind have more predictive ability than those using either one by itself. The change of the model parameters with time appears to be slow. This suggests that while the relationship of the mean square error and the resultant wind and wind speed is changing, it may not be necessary to update the model parameters in every period.

2. THE MODEL AND STATISTICAL PROCEDURE

Let $Y_i(t)$ denote the first-guess error at location i at time t ; $i = 1, \dots, L$. Let $\mathbf{x}_i(t) = (x_{ij}(t); j = 1, \dots, p)$ denote the covariates at location i at time t .

Consider the following model for the first-guess errors.

$$P\{Y_i(t) \in dy_i(t); i = 1, \dots, L | \mathbf{x}_i(t), \beta(t), y_j(s), \mathbf{x}_j(s), s < t, j = 1, \dots, L\} \\ = \prod_{i=1}^L \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2} \mathbf{x}_i(t) \beta(t)\right\} \exp\left\{-\frac{1}{2} y_i(t)^2 \exp\{-\mathbf{x}_i(t) \beta(t)\}\right\} dy_i(t) \quad (2.1)$$

where $\mathbf{x}_i(t) \beta(t) = \sum_{j=1}^p x_{ij}(t) \beta_j(t)$; that is, given $\beta(t)$, the first-guess errors are conditionally independent normally distributed with mean 0 and log linear variances

$$\sigma_i^2(t) = \exp\{\mathbf{x}_i(t) \beta(t)\} \quad (2.2)$$

independent of everything else.

The coefficients $\beta(t)$ are modeled as changing according to a random walk

$$\beta(t+1) = \beta(t) + \omega(t+1) \quad (2.3)$$

where $\{\omega(t)\}$ are independent multivariate normal random variables with variance-covariance matrices $\{W(t)\}$. The matrix $W(t+1)$ is independent of $\{Y_i(s), \mathbf{x}_i(s), \beta(s), s \leq t, i = 1, \dots, L\}$

In the next subsection we suggest a Kalman filter-like procedure to produce successive estimates of $\beta(t)$ as new data become available. The procedure is based on a Laplace approximation to an integral.

2.1 An approximate Updating Procedure

Assume the posterior distribution of $\beta(t)$ given $\{y_i(s), i = 1, \dots, L, s \leq t\}$ is multivariate normal with mean $\mathbf{m}(t)$ and variance-covariance matrix $\Sigma(t)$.

Since it is known that

$$\beta(t+1) = \beta(t) + \omega(t+1),$$

the prior distribution of $\beta(t+1)$ is multivariate normal with mean $\mathbf{m}(t)$ and variance-covariance matrix

$$\mathbf{R}(t) = \Sigma(t) + \mathbf{W}(t+1). \quad (2.4)$$

A description of the procedure used to determine $\mathbf{W}(t+1)$ appears in Section 3.

The forecast/prediction distribution of $\{Y_i(t+1); i = 1, \dots, L\}$ in terms of data up to time t and covariate values at time $t+1$ is

$$\begin{aligned} & P\{Y_i(t+1) \in dy_i; i = 1, \dots, L \mid Y_i(s), x_i(u), i = 1, \dots, L, s \leq t, u \leq t+1\} \\ &= \int \prod_{i=1}^L \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2} x_i(t+1) \mathbf{b}\right\} \exp\left\{-\frac{1}{2} y_i^2 \exp\{-x_i(t+1) \mathbf{b}\}\right\} f_{\beta(t+1)}(\mathbf{b}) d\mathbf{b} dy_i \end{aligned} \quad (2.5)$$

where

$$f_{\beta(t+1)}(\mathbf{b}) = \left((2\pi)^p \det R(t)\right)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2} (\mathbf{b} - \mathbf{m}(t)) R^{-1}(t) (\mathbf{b} - \mathbf{m}(t))'\right\}. \quad (2.6)$$

We now approximate the integral by the Laplace method; cf. Easton (1991), Cox and Hinkley (1974), de Bruijn (1958). Let the exponent of the integrand be

$$g(\mathbf{b}) = -\frac{1}{2} \left[\sum_{i=1}^L (\mathbf{x}_i \mathbf{b}) + y_i^2 \exp\{-\mathbf{x}_i \mathbf{b}\} + (\mathbf{b} - \mathbf{m}(t)) \mathbf{R}^{-1}(t) (\mathbf{b} - \mathbf{m}(t))' \right] + K \quad (2.7)$$

where K is a constant and we let $\mathbf{x}_i = \mathbf{x}_i(t+1)$. Differentiating, we obtain

$$\frac{\partial}{\partial b_j} g(\mathbf{b}) = -\frac{1}{2} \left[\sum_{i=1}^L x_{ij} [1 - y_i^2 \exp\{-\mathbf{x}_i \mathbf{b}\}] + 2\mathbf{R}_{j\cdot}^{-1}(t) (\mathbf{b} - \mathbf{m}(t)) \right] \quad (2.8)$$

where $\mathbf{R}_{j\cdot}^{-1}(t)$ denotes the j^{th} row of $\mathbf{R}^{-1}(t)$ and

$$\frac{\partial^2}{\partial b_j \partial b_k} g(\mathbf{b}) = -\frac{1}{2} \left[\sum_{i=1}^L y_i^2 \exp\{-\mathbf{x}_i \mathbf{b}\} x_{ij} x_{ik} + 2\mathbf{R}_{jk}^{-1} \right]. \quad (2.9)$$

Use a Newton procedure to solve the system of equations

$$0 = \frac{\partial}{\partial b_j} g(\mathbf{b}) \quad j = 1, \dots, p. \quad (2.10)$$

for $\mathbf{m}(t+1)$. Solve for $\Sigma(t+1)$ using the second derivatives of g evaluated at $\mathbf{m}(t+1)$; that is $\Sigma(t+1)$ is minus the inverse of the matrix whose (j, k) entry is

$$\frac{\partial^2}{\partial b_j \partial b_k} g(\mathbf{m}(t+1)). \quad (2.11)$$

The posterior distribution of $\beta(t+1)$ given $\{Y_i(s), \mathbf{x}_i(s), i = 1, \dots, L, s = 1, \dots, t+1\}$ is approximated by a multivariate normal distribution with mean $\mathbf{m}(t+1)$ and variance $\Sigma(t+1)$. The estimate of $\beta(t+1)$ is $\mathbf{m}(t+1)$.

The predicted mean square error for the i th location at time $t+2$ is

$$\exp\left\{\sum_{j=1}^p x_{ij}(t+2)m_j(t+1)\right\}.$$

3. DATA ANALYSIS

In this subsection we report results concerning using regression-like models for the mean square error of the first-guess with recursively updated parameter estimates to predict future mean-square errors of the first-guess.

The data consist of measurement and 12 hour forecasts (first-guess values) of u and v wind components at the 850 mb, 500 mb and 250 mb pressure levels from 93 stations in North America 25N–75N for the month of July 1991. The forecasts are produced using the NOGAPS Spectral Forecast Model; cf. Hogan et al., (1991). Each station has measurement and first-guess values for every 12 hours; there are some missing observations and suspicious values of wind components equal to 0. These missing and questionable values are deleted from the data set. The measurement values (if available) are subtracted from the first-guess values to obtain observations of the error of the first-guess value.

Let $U(0;t)$, (respectively $V(0;t)$), be the observed u -wind, (respectively v -wind) component at time t . Let $U(f;t)$, (respectively $V(f;t)$), be the first-guess u -wind (respectively v -wind) component at time t ; $U(f;t)$ is the forecasted value of $U(t)$ made 12 hours previously. The first-guess error for the u -wind component is

$$Y(t) = U(f;t) - U(0;t). \quad (3.1)$$

The following covariates are considered in the log-linear model for the mean square error of the first-guess.

$$r(0;t) = \left[(U(0;t) - U(0;t-1))^2 + (V(0;t) - V(0;t-1))^2 \right]^{\frac{1}{2}} \quad (3.2)$$

$$s(0;t) = \left[U(0;t)^2 + V(0;t)^2 \right]^{\frac{1}{2}} \quad (3.3)$$

$$r(f;t) = \left[(U(f;t) - U(f;t-1))^2 + (V(f;t) - V(f;t-1))^2 \right]^{\frac{1}{2}} \quad (3.4)$$

$$s(f;t) = \left[U(f;t)^2 + V(f;t)^2 \right]^{\frac{1}{2}}. \quad (3.5)$$

The resultant wind $r(0;t)$, (respectively $r(f;t)$), is a measure of the observed (respectively forecasted), change in the wind. The variable $s(0;t)$, (respectively $s(f;t)$), is the observed, (respectively forecasted), wind speed. Higher wind speeds suggest more activity in the atmosphere.

3.1 The Models

The following models for the mean square error are considered

One Variable Models: Observed Covariates

1. Given $\beta_0(t)$, $\beta_1(t)$, the first-guess errors at each location $\{Y_i(t); i = 1, \dots, L\}$ are independent normally distributed with mean 0. The variance of $Y_i(t)$ is the following function of the observed resultant wind at location i at time t , $r_i(0;t)$

$$\sigma_1^2(1;t;r_i(0;t)) = \exp\{\beta_0(t) + \beta_1(t)r_i(0;t)\} \quad (3.6)$$

where $r_i(0;t)$ is the observed resultant wind at location i at time t and $Y_i(t)$ is the first-guess error at location i at time t .

2. Given $\beta_0(t)$, $\beta_1(t)$, $\{Y_i(t); i = 1, \dots, L\}$ are independent normally distributed with mean 0. The variance of $Y_i(t)$ is the following function of the observed wind speed at location i at time t , $s_i(0;t)$

$$\sigma_2^2(1;t;s_i(0;t)) = \exp\{\beta_0(t) + \beta_1(t)s_i(0;t)\} \quad (3.7)$$

where $s_i(0;t)$ is the observed wind speed at location i at time t .

Two-variable Model, Observed Covariates

3. Given $\beta_0(t)$, $\beta_1(t)$, $\beta_2(t)$, $\{Y_i(t); i = 1, \dots, L\}$ are independent normally distributed with mean 0. The variance of $Y_i(t)$ is the following function of both the resultant wind and wind speed at location i at time t

$$\sigma_2^2(t; r_i(0;t); s_i(0;t)) = \exp\{\beta_0(t) + \beta_1(t)r_i(0;t) + \beta_2(t)s_i(0;t)\}. \quad (3.8)$$

Similar one-variable and two-variable models but using first-guess values of the covariates are also considered. In all cases the first-guess error and the covariates are all evaluated at the same pressure level.

The regression parameters $\beta(t)$ are assumed to evolve according to the random walk given by (2.3)

3.2 The Data Analysis

The results of Jacobs and Gaver (1992) suggest that of the models using observed values for covariates, the models for the 850 mb pressure level have the most predictive value. It is also suggested that of the models using first-guess values for covariates, the models for the 250 mb pressure level have the most predictive ability. As a result in what follows we will restrict our attention to these two cases.

a. Estimation and Prediction of 850 mb First-guess Mean Square Errors using Observed Wind Covariates.

The estimation procedure described in Section 2 was used to recursively estimate the regression parameters $\beta(t)$ for each of models (3.6) – (3.8) for 850 mb first-guess errors using observed 850 mb wind covariates. The initializing estimates of $\beta(t)$ are the estimates obtained using all April data recorded in

Jacobs and Gaver (1992); the initial variance-covariance matrix is the identity matrix. The estimates from April are used since April appeared to have more predictive ability for July than February, cf. Jacobs and Gaver (1992).

The variance-covariance matrix of the innovation W_t of the random walk (2.3) was taken to be a constant times the identity matrix. Preliminary explorations based on values of the predictive log-likelihood using different values of the constant suggest that for purposes of prediction, the constant should be very small. In what follows we set the constant equal to 0.

Figure 1, (respectively Figure 2) presents plots of the estimates of the slopes, e.g., $\beta_1(t)$ and $\beta_2(t)$, as a function of time which is labeled 1, 2, for u -wind (respectively v -wind) component error.

Figure 1 presents the values of estimates of the parameter multiplying $r_i(0;t)$ (respectively $s_i(0;t)$) for the one parameter models (3.6) and (3.7) in the upper graph. The lower graph presents the values of the estimates of the parameter multiplying $r_i(0;t)$, (respectively $s_i(0;t)$) for the two-variate model. There appears to be a slight trend in the estimates.

Figure 2 presents the values of the estimate of the parameters multiplying $r_i(0;t)$, (respectively $s_i(0;t)$) as o , (respectively $+$), for the respective one-variate models. The values of the estimates of the parameters multiplying $r_i(0;t)$, (respectively $s_i(0;t)$) for the two-variate model are presented as \times (respectively ∇) for each time t . These graphs suggest more evidence of a trend in the estimates. Note that the estimates of the slopes are positive. Hence increased values of the resultant wind $r_i(0;t)$ and/or wind speed $s_i(0;t)$ are associated with increased variance of the first-guess value. This is plausible physically,

since a large value of $r_i(0;t)$ is indicative of a change in the atmosphere and a large value of $s_i(0;t)$ is indicative of greater activity in the atmosphere.

To assess the predictive ability of the models, the models with parameters estimated at time t are used to forecast the variances of the first-guess errors at time $t+1$.

One procedure to informally assess the predictive ability of the models is by binning the data. To assess models (3.6) and (3.8) the data $(y_i(t), r_i(0;t), s_i(0;t))$ are binned into 10 bins based on ordering the values of $r_i(0;t)$ for all time t from smallest to largest. The data in the first bin correspond to the smallest values of $r_i(0;t)$; the data in the 10th bin correspond to the largest values of $r_i(0;t)$. Each bin contains about 1/10th of the data with the 10th bin containing a few more data. The averages of the predictive variances for models (3.6) and (3.8) are computed for each bin. The average $y_i(t)^2$ is also computed for each bin.

To assess models (3.7) and (3.8) the same procedure is used but the binning is based on the values of $s_i(0;t)$.

Figures 3 and 4 present graphs of the $\log[\text{average } y_i(t)^2]$ in each bin versus $\log[\text{average predictive variance}]$ in each bin for models (3.6) and (3.8) and models (3.7) and (3.8). If a model were perfect, the points should be close to the 45° line shown.

The figures suggest that of the two one-variate models, the one using the resultant wind $r_i(0;t)$ has the better predictive ability. The two-variate model appears to have similar predictive ability to the model using only $r_i(0;t)$.

Another procedure to assess predictive ability is to compute the log-likelihood using estimated values of $\beta(t)$ (eg. $\mathbf{m}(t)$) in the term for the first

guess errors at time $t+1$. Larger values of the (predictive) log-likelihood indicate better predictive ability. The (predictive) log-likelihood up to addition and multiplication by constants is

$$\tilde{l} = -\sum_{t=1}^{T-1} \left[\sum_{i=1}^L x_i(t+1)m(t) + \sum_{i=1}^L y_i^2(t+1)\exp\{-x_i(t+1)m(t)\} \right]. \quad (3.9)$$

Table 1 presents values of \tilde{l} for the one-time step ahead predictions of the variance; these values appear in the column *Iterative*. Also displayed are the values of \tilde{l} obtained by estimating the parameters once using all the data; this value of \tilde{l} is a goodness-of-fit value and appears in the column labeled *All*; the estimates used to obtain the goodness-of-fit value of \tilde{l} are those appearing for July in Table 7 of Jacobs and Gaver (1992).

Four models are considered: constant variance (no dependence on variables), two one-variate models (3.6) and (3.7) and the two-variate model (3.8). The parameter of the constant variance model using all the data is estimated using maximum likelihood; this estimate is used to calculate the goodness-of-fit value of \tilde{l} for the constant variance model.

The goodness-of-fit constant variance value of \tilde{l} is smaller than the prediction values of \tilde{l} using models with covariates. This behavior indicates that the covariates do have predictive ability. The prediction value of \tilde{l} for the two-variate prediction model is larger than that for either one-variate model indicating that both covariates have some predictive ability. Of the two one-variate models, the one using $r_i(0;t)$ has the larger prediction value of \tilde{l} . The closeness of the prediction values of \tilde{l} obtained by iteratively updating the estimates and using them to predict variance of the next time period and the goodness-of-fit values of \tilde{l} obtained by using model

parameters estimated from all the data suggest that the updating procedure is doing very well. Note that for the one-variate model using $r_i(0;t)$, the prediction values of \tilde{l} are larger than the goodness-of-fit values of \tilde{l} ; this suggests that there is systematic change in the values of β over time for this model.

TABLE 1
VALUE OF LOG-LIKELIHOOD OBSERVED COVARIATES, 850 mb

Data	Model	Iterative (Prediction)	All (Goodness-of-Fit)
<i>u</i> -wind	<i>Constant Variance</i>	-9610.7	-9510.0
	<i>One-variate</i>		
	$r(0;t)$	-8544.1	-9098.3
	$s(0;t)$	-8607.9	-8596.2
	<i>Two-variate</i>	-8489.2	-8467.5
<i>v</i> -wind	<i>Constant Variance</i>	-9692.7	-9620.2
	<i>One-variate</i>		
	$r(0;t)$	-8730.9	-9294.1
	$s(0;t)$	-8769.2	-8756.5
	<i>Two-variate</i>	-8663.8	-8652.4

b. Estimation and Prediction of First-guess Mean Square Errors using First-guess Wind Covariates

The recursive estimation procedure in Section 2 was used to estimate the regression parameters $\beta(t)$ for each of models (3.6) – (3.8) for 250 mb first-guess errors using first-guess 250 mb wind covariates; that is, the first-guess wind speed at location i at time t at the 250 mb level, $s_i(f;t)$ replaces $s_i(0;t)$, etc. The initializing estimates of $\beta(t)$ are the estimates obtained using all April data recorded in Jacobs and Gaver (1992); the initial variance-covariance matrix is the identity matrix. The estimates from April are used since April appears to have somewhat more predictive ability than February for July; Jacobs and Gaver (1992).

Once again, preliminary exploratory work using the resulting value of the predictive log-likelihood indicates that setting the variance-covariance matrix of the innovation of the random walk equal to 0 gives the best predictions. This suggests that the change in the relationship of the mean square error and the covariates is slow.

Figure 4, (respectively Figure 5) presents plots of the values of the estimates for the 250 mb u -wind component errors and the 250 mb v -wind component errors. The values of the estimates multiplying $r(f;t)$, (respectively $s(f;t)$) are represented by o , (respectively $+$) for the one-variate models. For the two-variate model, the estimates multiplying $r(f;t)$, (respectively $s(f;t)$) are presented as \times , (respectively ∇). The figures suggest evidence of a trend in the estimates. Note that once again all the estimates are positive. Thus, increased first-guess resultant wind and/or wind speed tends to increase the mean square error

To assess the predictive ability of the models, the models with parameters estimated at time t are used to forecast the variances of the first-guess errors at time $t+1$.

One procedure to informally assess the predictive ability of the models is by binning the data. The data are binned as in the previous subsection. Figures 7 and 8 present graphs of the log [average $y_i(t)^2$] in each bin versus log [average predicted variance] in each bin for models (3.6) and (3.8) and models (3.7) and (3.8). If a model were perfect, the points should be close to the 45° line shown.

Table 2 presents values of \tilde{l} , given by (3.9), for the one-time step ahead prediction of variance; these values appear in the column iterative. Also

displayed are the values of \tilde{l} obtained by estimating the model parameters once using all the data; this value of \tilde{l} is a measure of goodness-of-fit and appears in the column labeled All; the estimates used in regressions with covariates for the goodness-of-fit evaluation of \tilde{l} are those appearing for July in Table 11 of Jacobs and Gaver (1992). The constant variance estimate using all the data is the maximum likelihood estimate. The results for four models are presented; constant variance models, one-variate models (3.6) and (3.7), and the two-variate model (3.8).

Note that all of the iterative prediction values of \tilde{l} for the models with covariates are larger than those for the constant variance goodness-of-fit value; this suggests that the covariates have some predictive value.

The iterative prediction value of \tilde{l} for the one-variate model using $r(f;t)$ is greater than the goodness-of-fit value obtained by using parameters estimated using all the data; this suggests that there is a systematic change in the model parameter values over time. For the other regressions using covariates the prediction values of \tilde{l} are smaller than their corresponding goodness-of-fit values but not by much. The model that maximizes the prediction values of \tilde{l} is the two-variate model suggesting that both covariates have some predictive value..

Figures 9 and 10 and Table 3 present results for models of the variance of the first-guess error at 500 mb level using 500 mb first-guess covariates. The implications of the results are similar to those of the 250 mb results. The predictive ability of the recursively estimated two-variate model appears somewhat greater at the 250 mb level than the 500 mb level; this conclusion is based on the values of $(\tilde{l}_2 - \tilde{l}_c)/\tilde{l}_c$ where \tilde{l}_2 is the prediction value of \tilde{l} for the two-variate model and \tilde{l}_c is the goodness-of-fit value of \tilde{l} for the constant variance model; the value of this fraction is larger for 250 mb than for 500 mb.

TABLE 2
VALUE OF LOG-LIKELIHOOD FIRST-GUESS COVARIATES, 250 mb

Data	Model	Iterative (Prediction)	All (Goodness-of-Fit)
<i>u</i> -wind	<i>Constant Variance</i>	-14,589.4	-14,516.5
	<i>One-variate</i>		
	<i>r(f;t)</i>	-13,640.6	-14,474.7
	<i>s(f;t)</i>	-13,598.3	-13,575.5
	<i>Two-variate</i>	-13,599.5	-13,579.4
<i>v</i> -wind	<i>Constant Variance</i>	-14,429.1	-14,363.1
	<i>One-variate</i>		
	<i>r(f;t)</i>	-13,389.2	-14,270.1
	<i>s(f;t)</i>	-13,388.4	-13,363.8
	<i>Two-variate</i>	-13,351.1	-13,329.6

TABLE 3
VALUE OF LOG-LIKELIHOOD FIRST-GUESS COVARIATES, 500 mb

Data	Model	Iterative (Prediction)	All (Goodness-of-Fit)
<i>u</i> -wind	<i>Constant Variance</i>	-11,237.3	-11,213.5
	<i>One-variate</i>		
	<i>r(f;t)</i>	-10,561.2	-11,176.8
	<i>s(f;t)</i>	-10,518.7	-10,499.6
	<i>Two-variate</i>	-10,520.0	-10,489.0
<i>v</i> -wind	<i>Constant Variance</i>	-11,204.0	-11,160.9
	<i>One-variate</i>		
	<i>r(f;t)</i>	-10,431.0	-11,118.2
	<i>s(f;t)</i>	-10,423.0	-10,411.9
	<i>Two-variate</i>	-10,411.8	-10,393.3

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850 MB U WIND

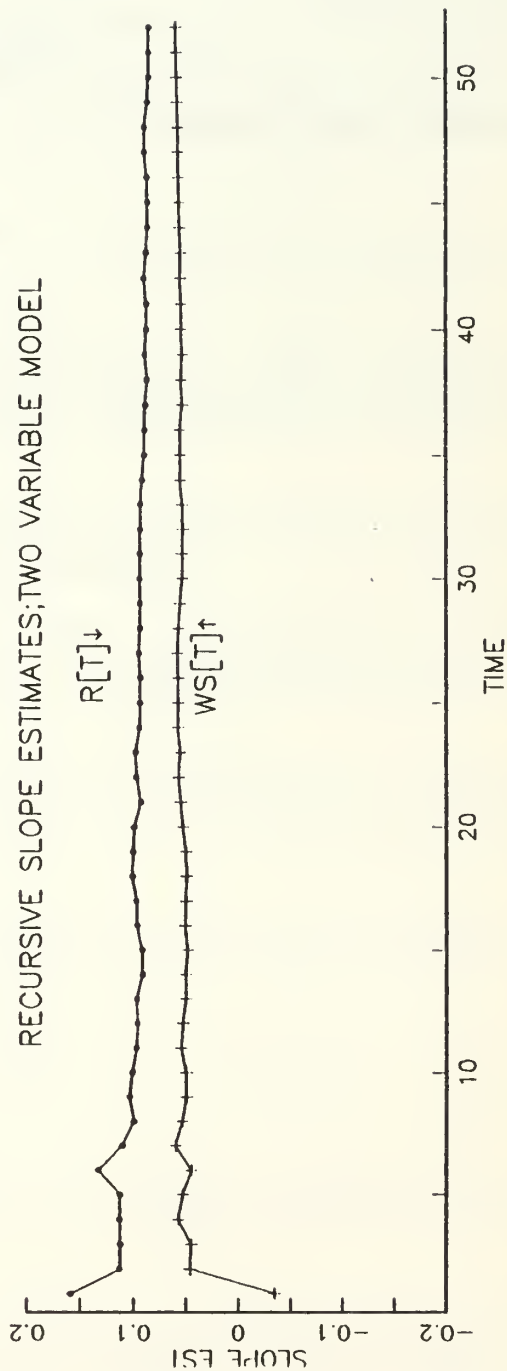
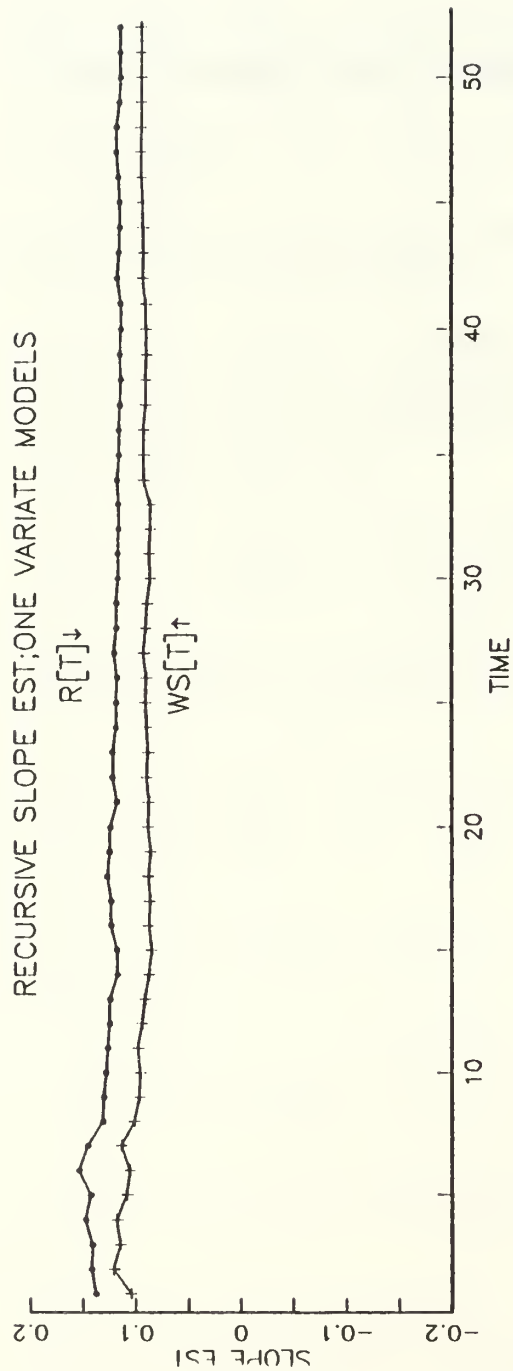


Figure 1

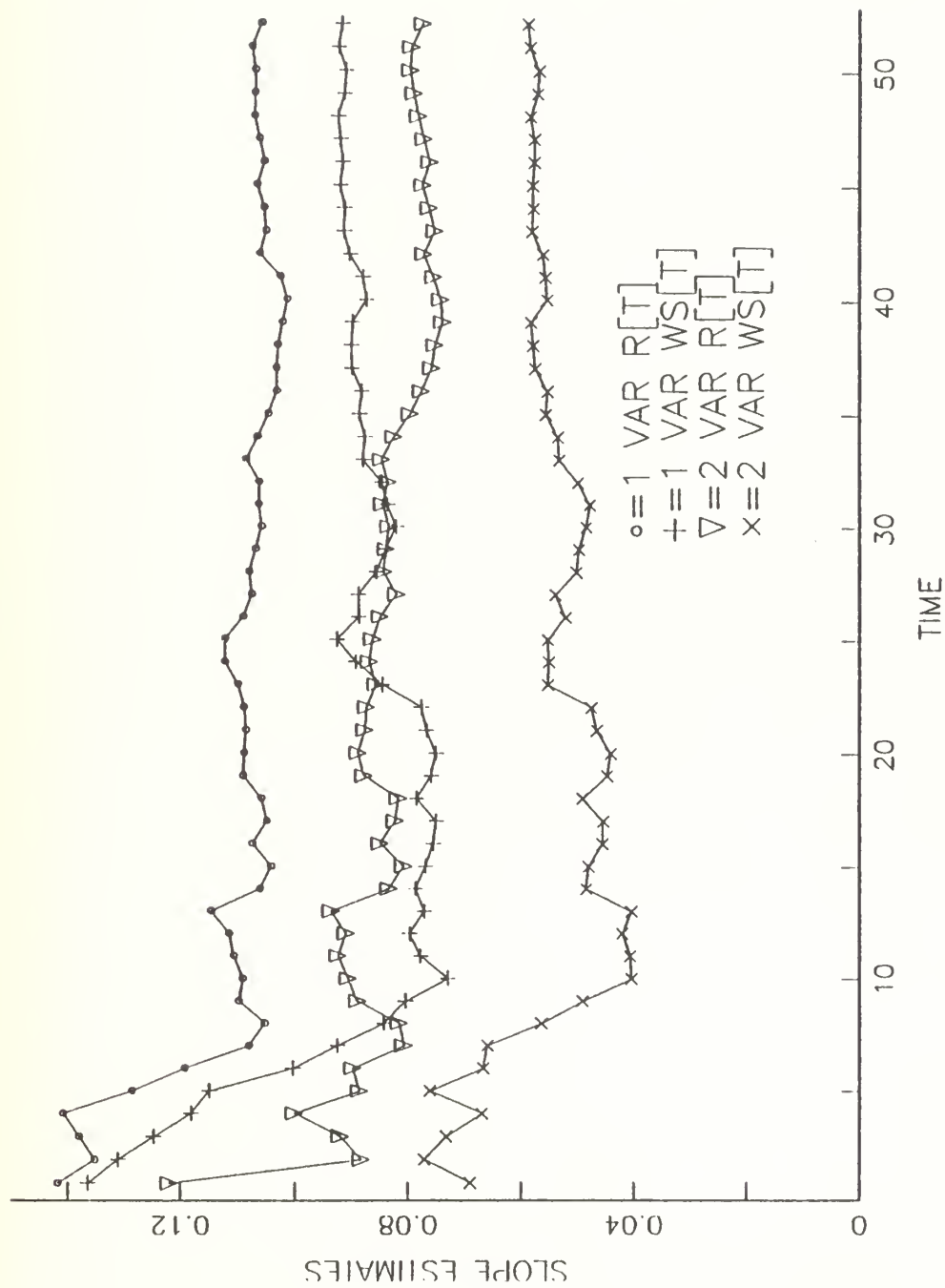
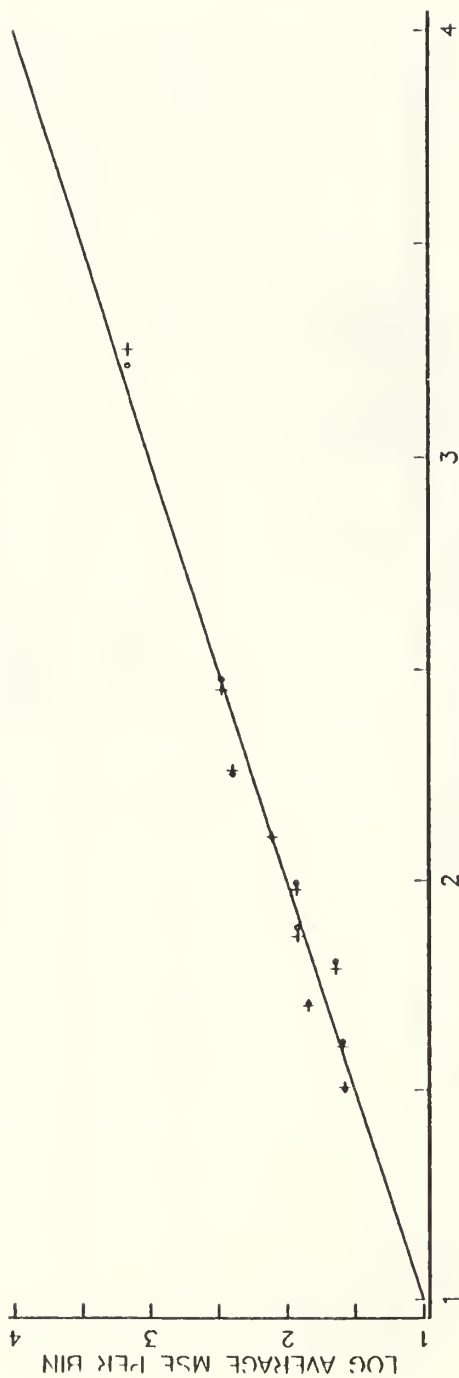


Figure 2

850 MB U WIND; RECURSIVE ESTIMATES; OBS WIND

1VAR=R[T]=0;2 VAR=+;BIN ON R[T]



1VAR=WS[T]=0;2 VAR=+;BIN ON WS[T]

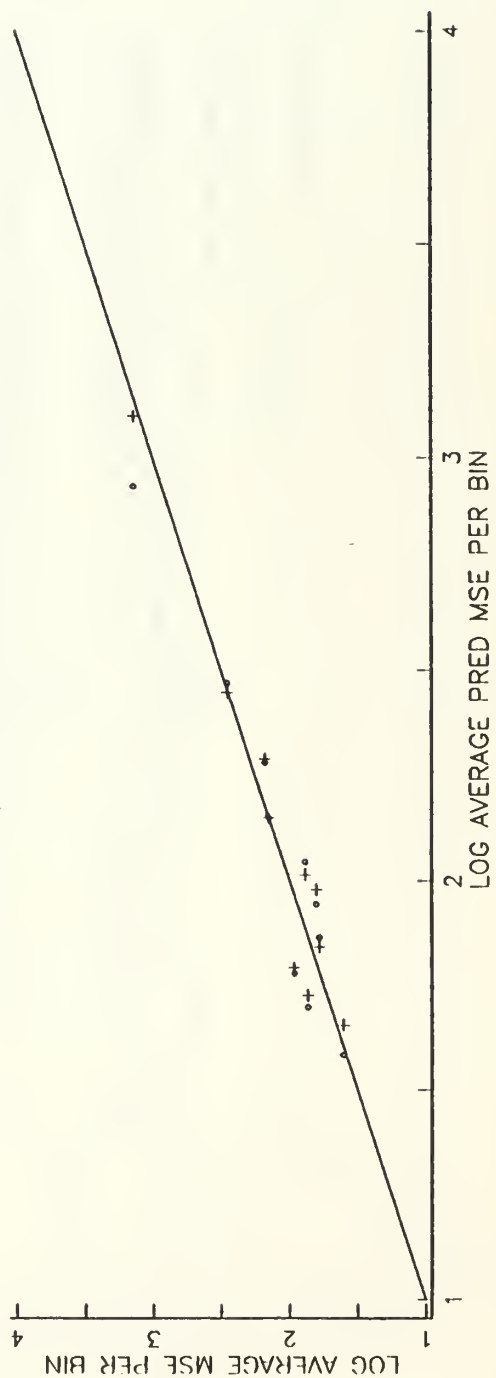
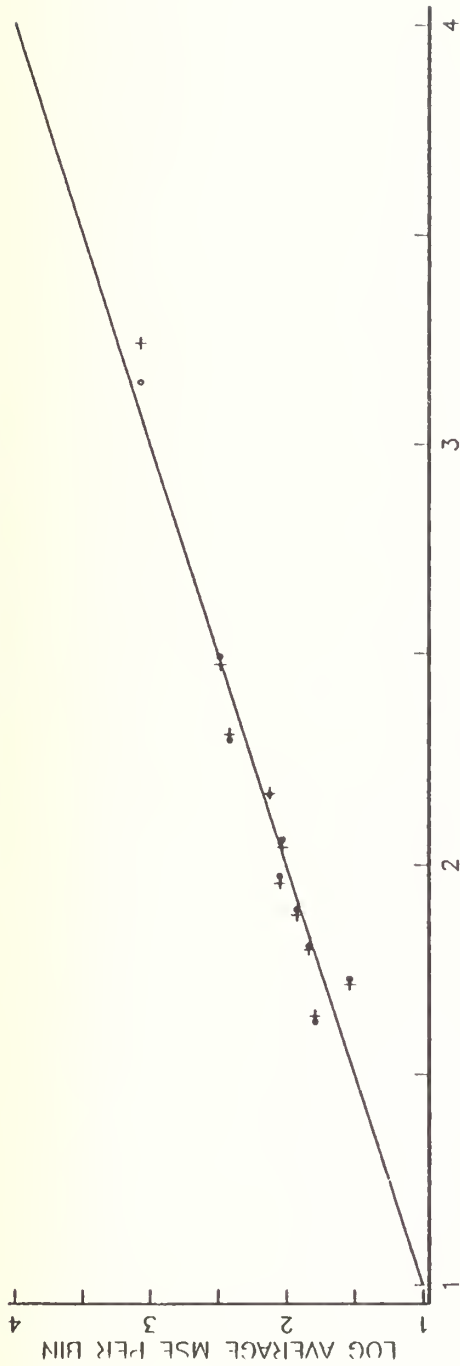


Figure 3

850 MB V WIND; RECURSIVE ESTIMATES; OBS WIND

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1 VAR=WS[T]=o;2 VAR=+;BIN ON WS[T]

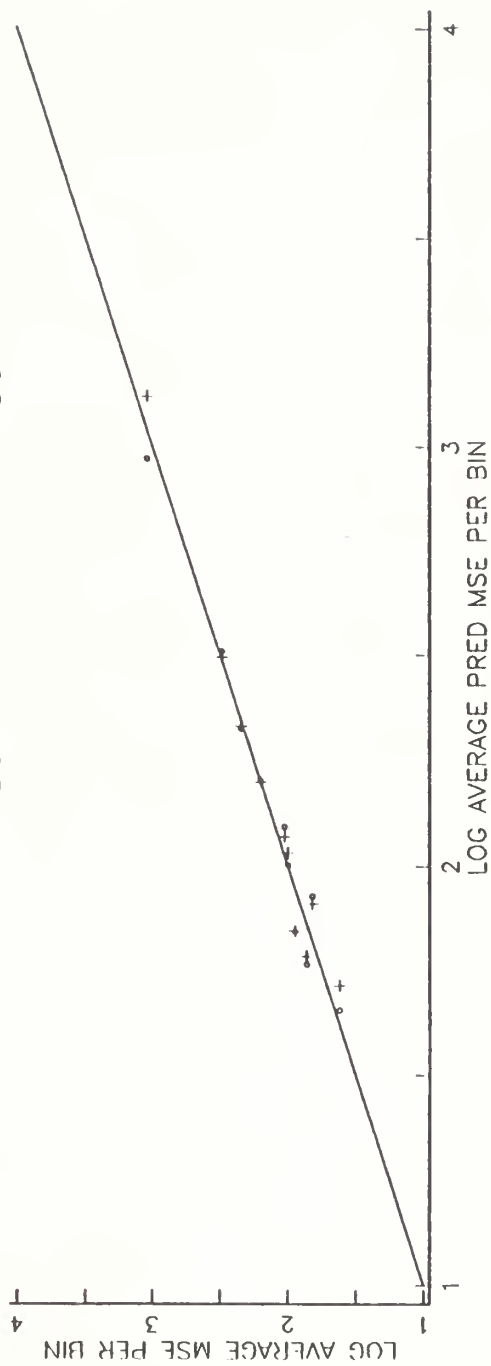


Figure 4

250 MB U WIND; RECURSIVE ESTIMATES; 1ST GUESS

1 VAR=WS[T]=o; 2 VAR=+; BIN ON WS[T]

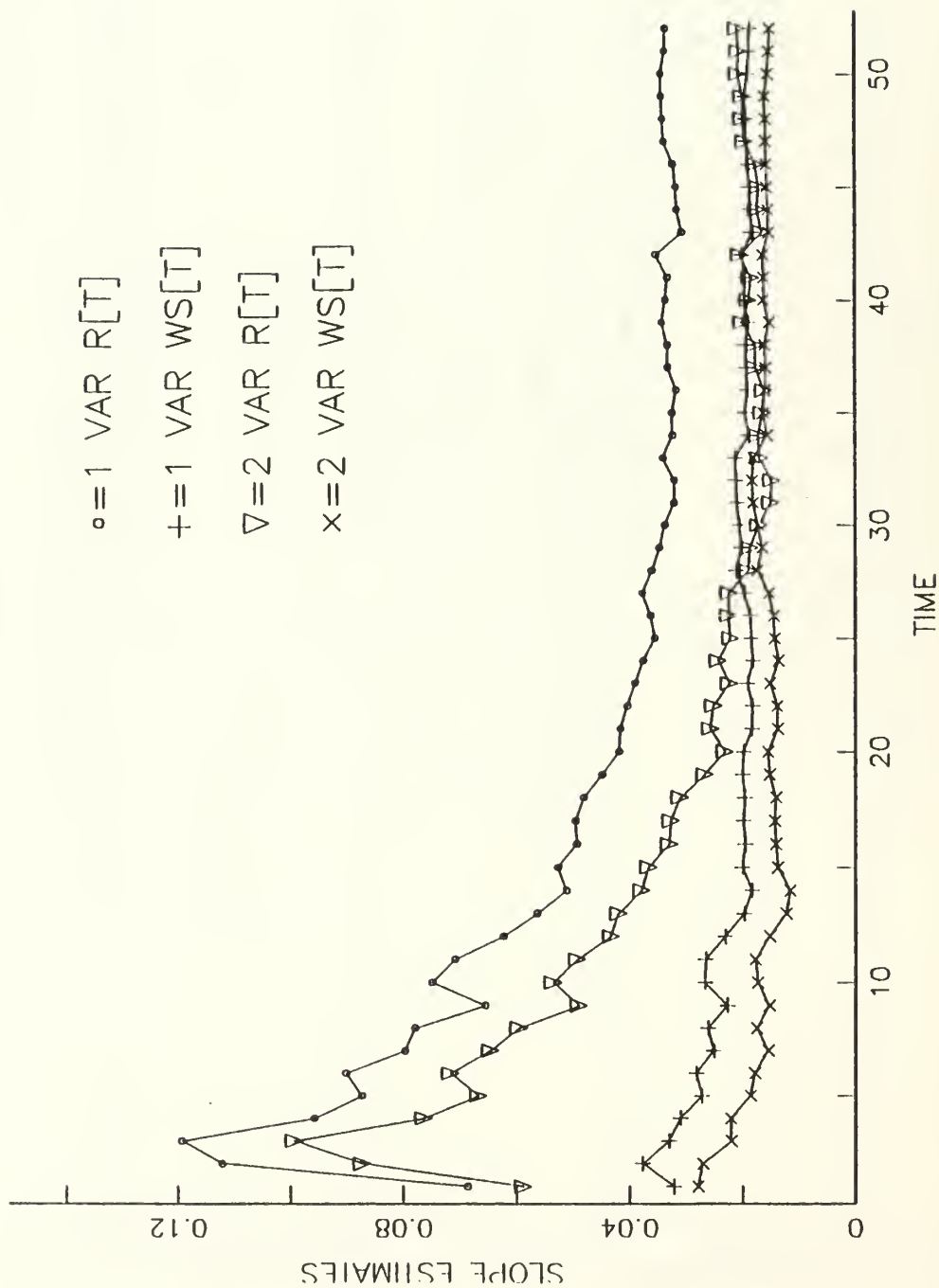


Figure 5

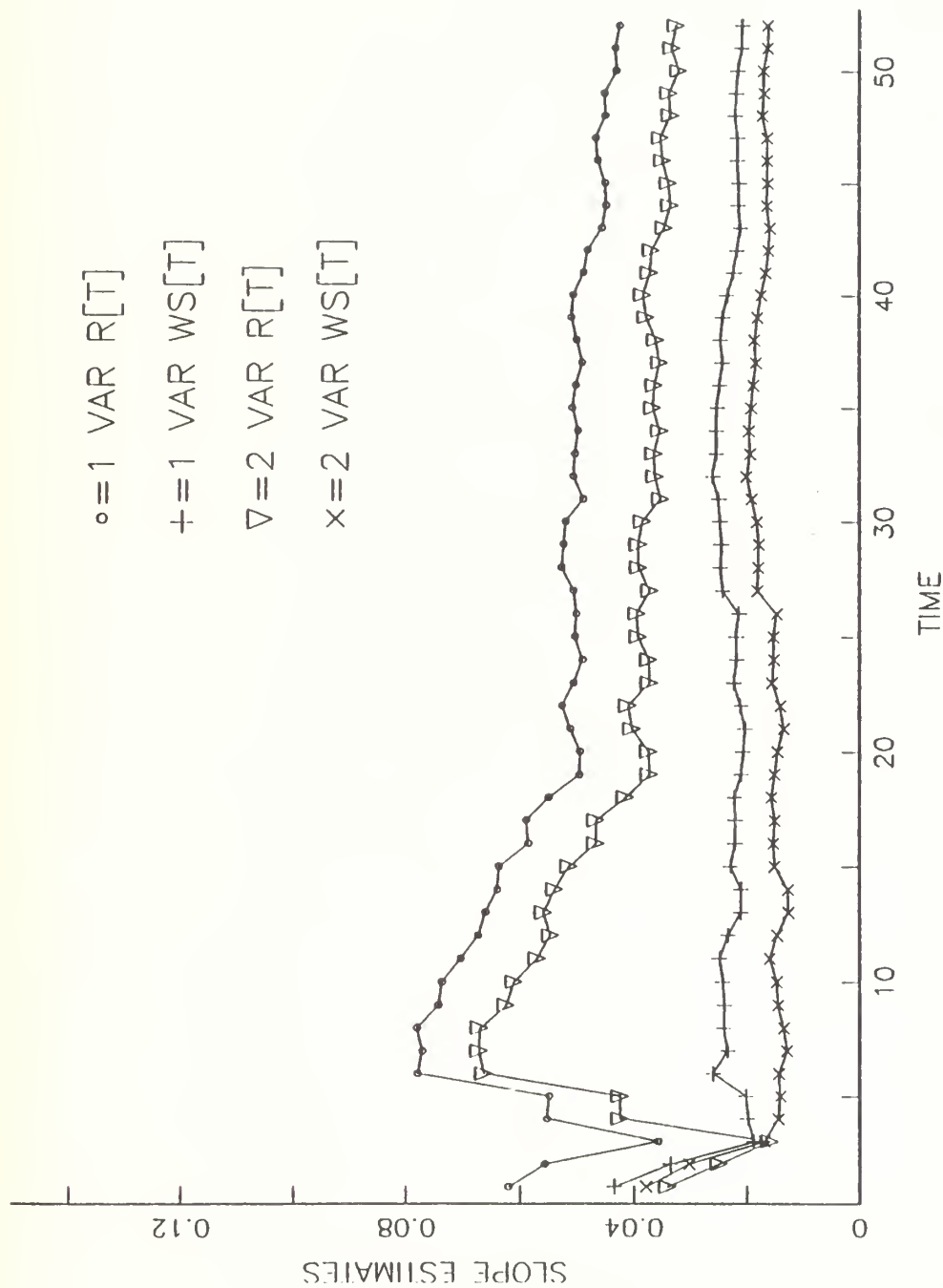
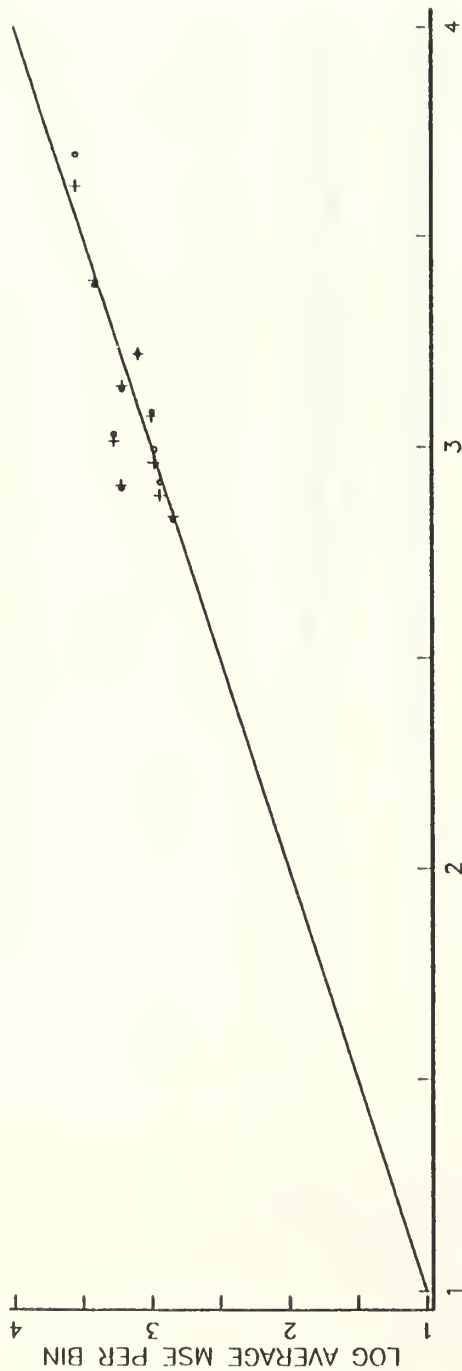


Figure 6

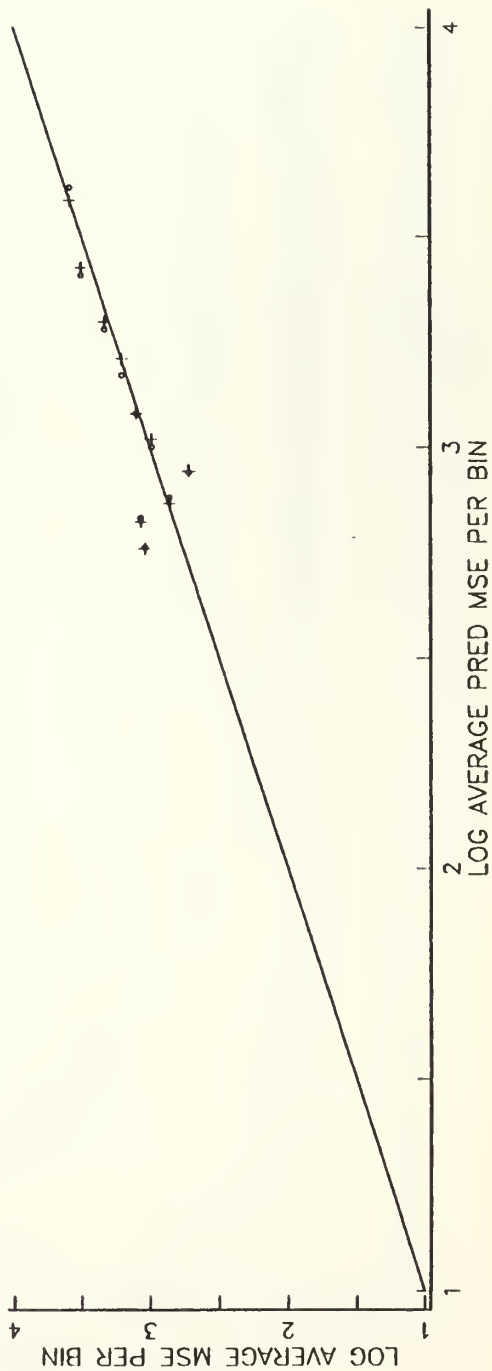
250 MB U WIND; RECURSIVE ESTIMATES; 1ST GUESS

1 VAR=R[T]=o; 2 VAR=+:BIN ON R[T]



2 LOG AVERAGE PRED MSE PER BIN

1 VAR=WS[T]=o; 2 VAR=+:BIN ON WS[T]

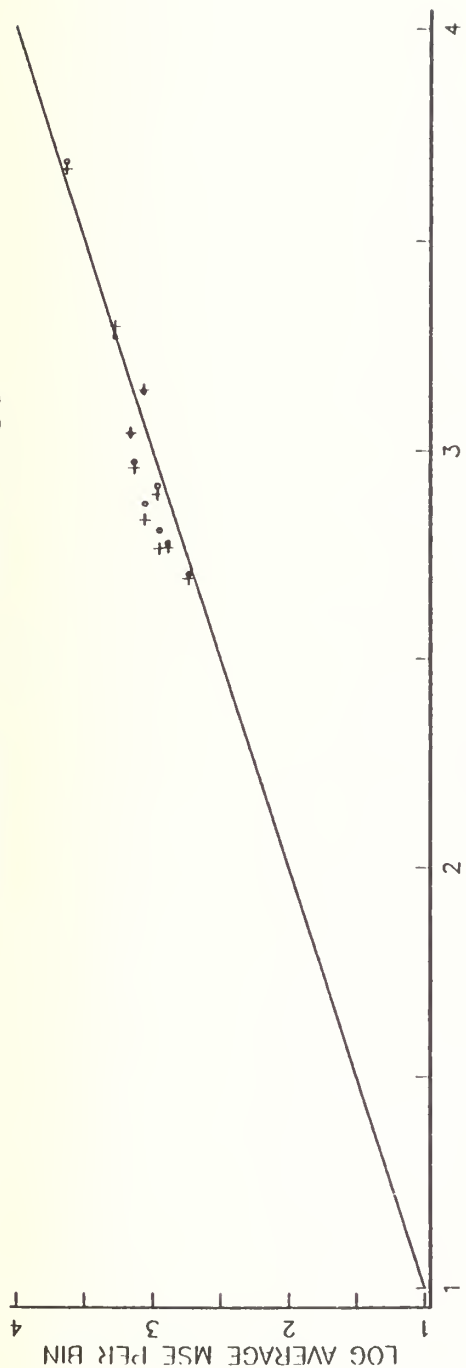


2 LOG AVERAGE PRED MSE PER BIN

Figure 7

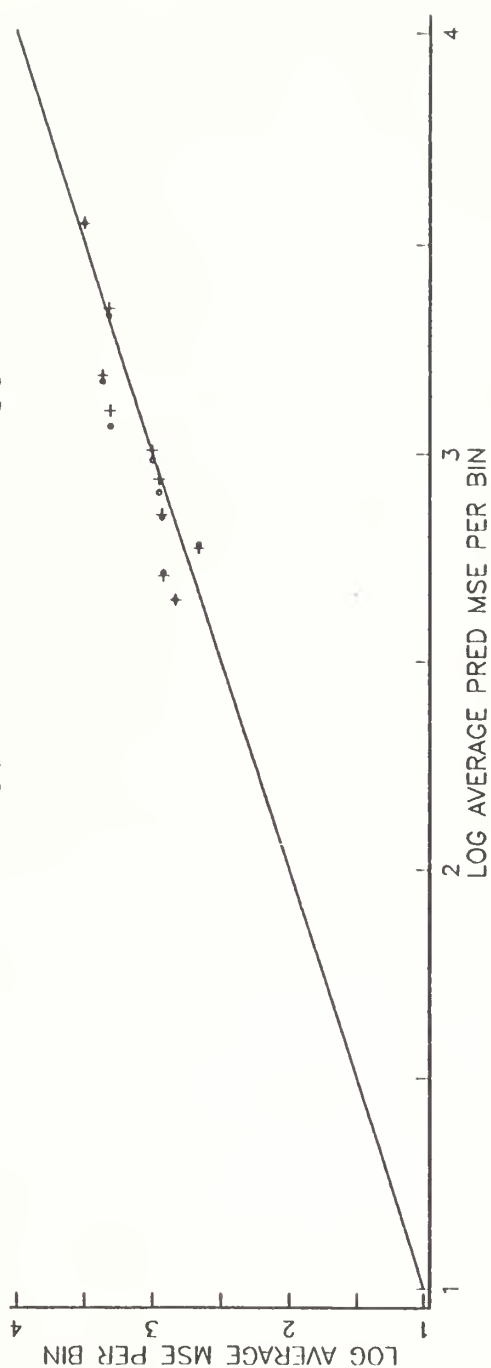
250 MB V WIND; RECURSIVE ESTIMATES; 1ST GUESS

1 VAR=R[T]=0; 2 VAR=+; BIN ON R[T]



2 LOG AVERAGE PRED MSE PER BIN

1 VAR=WS[T]=0; 2 VAR=+; BIN ON WS[T]

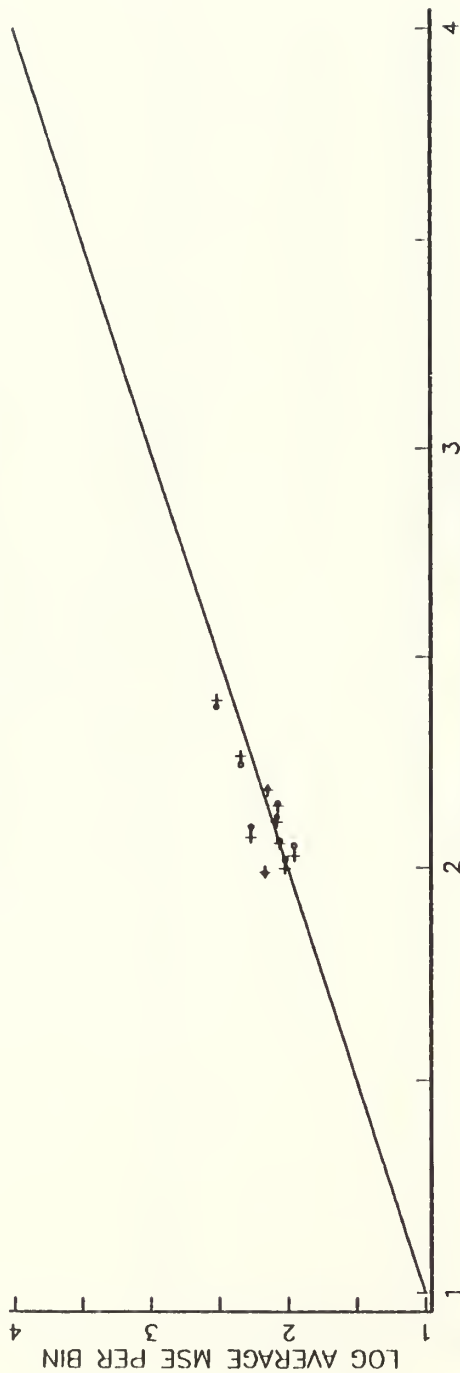


2 LOG AVERAGE PRED MSE PER BIN

Figure 8

500 MB U WIND; RECURSIVE ESTIMATES; 1ST GUESS

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2 LOG AVERAGE PRED MSE PER BIN
1 VAR=WS[T]=0; 2 VAR=+; BIN ON WS[T]

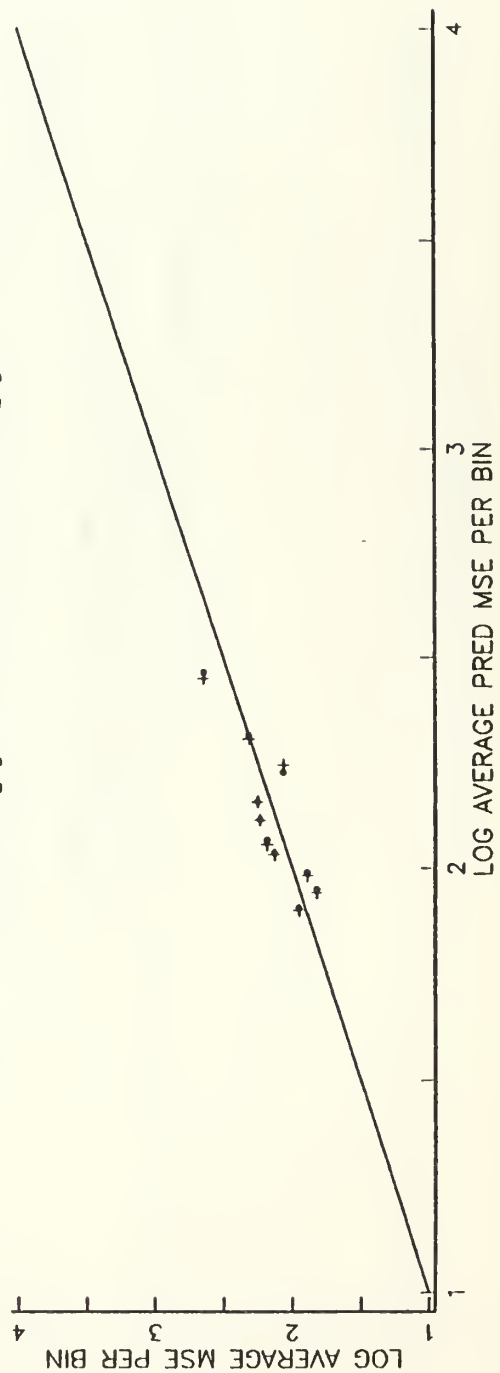
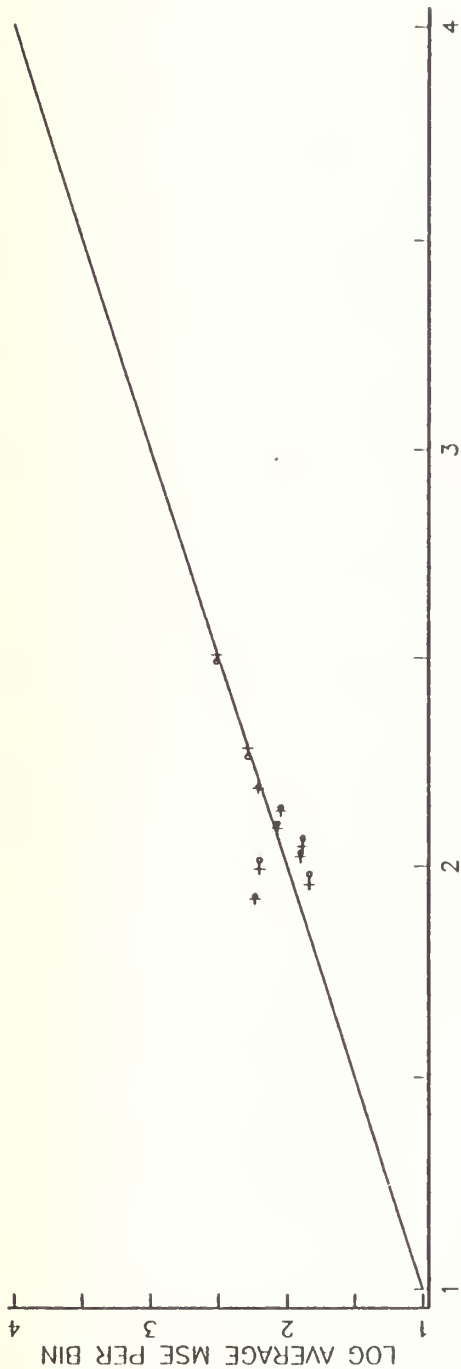


Figure 9

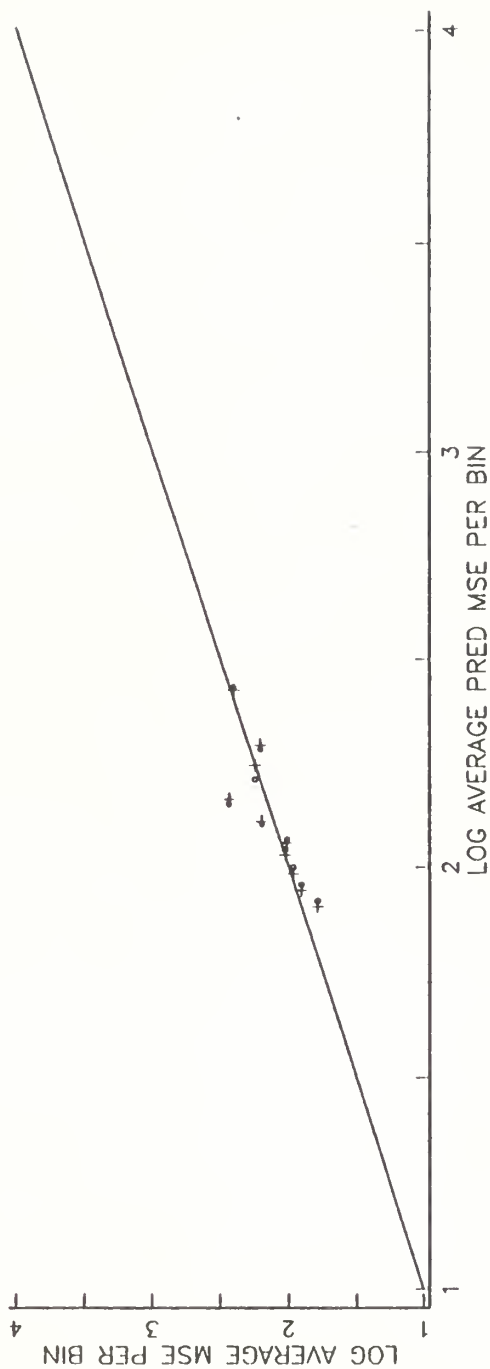
500 MB V WIND; RECURSIVE ESTIMATES; 1ST GUESS

1 VAR=R[T]=0; 2 VAR=+; BIN ON R[T]



2 LOG AVERAGE PRED MSE PER BIN

1 VAR=WS[T]=0; 2 VAR=+; BIN ON WS[T]



2 LOG AVERAGE PRED MSE PER BIN

Figure 10

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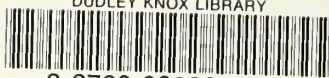
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